AON: Towards Arbitrarily-Oriented Text Recognition

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Motivation

OCR in Practice

- Uneven lighting, blurring
- Perspective distortion
- Orientation
- Most traditional OCR system deals with regular tightly-bounded, horizontal texts

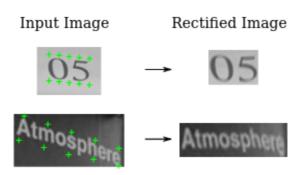


Previous Work I

Spatial Transformer Network Based Model

- The model learns to rectify input image, rotation, etc.
- Hard to optimize transformation network without geometric groundtruth
- Requires tricks on initialisation of model weights to guarantee training convergence

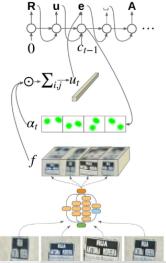
Previous Work II



Previous Work III

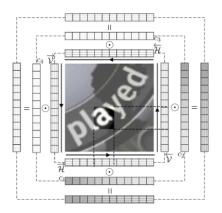
Attention Based Model

- Encode image into featuremap and use RNN to predict character sequences.
- Does not work well when directly applied to irregular texts

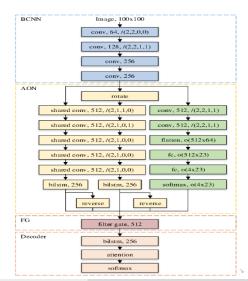


Method Intuition

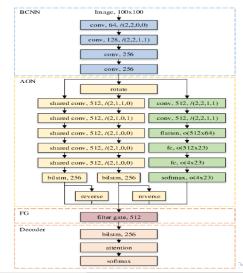
• Extract feature of four direction and learn to weight them properly



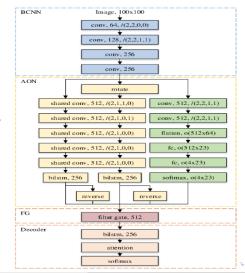
 Basal CNN(BCNN): extract low level image features



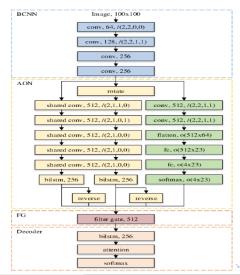
- Basal CNN(BCNN): extract low level image features
- Arbitrary(AON): extract high level features in 4 direction and calculate character placement clue



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- Filter Gate (FG): Combine the 4 features with the character placement clue

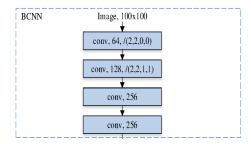


- Basal CNN(BCNN): extract low level image features
- Arbitrary(AON): extract high level features in 4 direction and calculate character placement clue
- Filter Gate (FG): Combine the 4 features with the character placement clue
- Attention-based Decoder: predict character sequence from the combined features



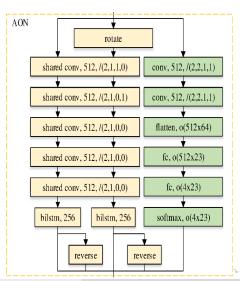
Basal CNN

- Simple stacked CNN
- The output must be square feature maps



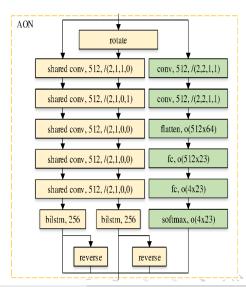
AON I

- Consider "left to right": stacked CNN downsamples the input feature maps from original dimension HxWxC to $1 \times L \times D$
- Then feed the feature map to a bidirectional lstm to further encode the feature sequence (keeping the same dimension)
- "right to left" feature is just the reverse of "left to right" feature (which accelerates training convergence)



AON II

- For "Up to down", just rotate the input by 90 degree
- At the end we have 4 L × D feature maps
- In practice, horizontal and vertical CNN share parameters to avoid unbalanced orientation in the dataset
- The character placement clue network uses CNN-FC to calculate 4 × L weight



Filter Gate

- Weighted sum of the 4 L × D features with the 4 × L weights to get a L × D feature and then activate by tanh function
- FG filter gate, 512

• For $i=1,\ldots,L$ $\widehat{h_i}'=[\overrightarrow{\mathcal{H}_i},\overleftarrow{\mathcal{H}_i},\overrightarrow{\mathcal{V}_i},\overleftarrow{\mathcal{V}_i}]c_i$ $\widehat{h_i}'=\tanh(\widehat{h_i}')$ $(\overrightarrow{\mathcal{H}_i}:D\times 1,c_i:1\times 4)$

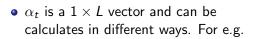
Attention Decoder

 Given previous output y_{t-1}, calculate the decoder input g_t, next state s_t and next output y_t as:

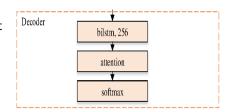
$$g_t = \sum_{j=1}^{L} \alpha_{t,j} \hat{h}_j$$

$$s_t = RNN(y_{t-1}, g_t, s_{t-1})$$

$$y_t = softmax(W^T s_t)$$



$$\alpha_{t,j} = s_{t-1}^T M h_j$$



Dataset

Name	Size	Irregular	with lexicon
SVT-Perspective	639	yes	50
CUTE80	288	yes	N/A
ICDAR 2015	2,077	yes	N/A
IIIT5K-Words	3,000	no	50,1000
Street View	647	no	50
ICDAR 2003	867	no	50, Full

Trained on 12-million synthetic dataset.



Experiment Result I

Method	SVT-Perspective			CT80	IC15	
Method	50	Full	None	None	None	
ABBYY[35]	40.5	26.1	_	_	_	
Mishra et al.[11]	45.7	24.7	_	_	-	
Wang et al.[37]	40.2	32.4	_	-	_	
Phan et al.[28]	75.6	67.0	_	_	-	
Shi <i>et al</i> .[31]	92.6	72.6	66.8	54.9	-	
Shi et al.[32]	91.2	77.4	71.8	59.2	_	
Yang et al.[39]	93.0	80.2	75.8	69.3	_	
Cheng et al.[6]	92.6	81.6	71.5	63.9	66.2	
Naive_base	92.4	83.3	70.5	75.4	67.8	
STN_base	94.6	82.8	68.5	73.7	67.5	
Ours	94.0	83.7	73.0	76.8	68.2	

Performance on irregular datasets.



Experiment Result II

Method	IIIT5k			SVT		IC03		
Method	50	1k	None	50	None	50	Full	None
ABBYY[35]	24.3	_	-	35.0	-	56.0	55.0	-
Wang et al. [35]	_	_	-	57.0	-	76.0	62.0	_
Mishra et al.[11]	64.1	57.5	-	73.2	-	81.8	67.8	_
Wang et al.[37]	_	_	-	70.0	-	90.0	84.0	-
Goel et al.[8]	_	_	-	77.3	-	89.7	_	_
Bissacco et al.[4]	_	_	-	90.4	78.0	_	_	_
Alsharif [2]	_	_	-	74.3	-	93.1	88.6	_
Almazán et al.[1]	91.2	82.1	-	89.2	-	_	_	-
Yao et al.[40]	80.2	69.3	-	75.9	-	88.5	80.3	_
Jaderberg et al.[16]	-	_	-	86.1	-	96.2	91.5	-
Su and Lu[33]	_	_	-	83.0	-	92.0	82.0	_
Gordo[9]	93.3	86.6	-	91.8	-	_	_	_
Jaderberg et al.[17]	97.1	92.7	-	95.4	80.7	98.7	98.6	93.1
Jaderberg et al.[16]	95.5	89.6	-	93.2	71.7	97.8	97.0	89.6
Shi et al.[31]	97.6	94.4	78.2	96.4	80.8	98.7	97.6	89.4
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Lee et al.[22]	96.8	94.4	78.4	96.3	80.7	97.9	97.0	88.7
Yang et al.[39]	97.8	96.1	-	95.2	-	_	97.7	-
Cheng's baseline[6]	98.9	96.8	83.7	95.7	82.2	98.5	96.7	91.5
Cheng et al.[6]	99.3	97.5	87.4	97.1	85.9	99.2	97.3	94.2
Naive_base	99.5	98.1	86.0	96.9	81.9	98.5	96.5	90.5
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Ours	99.6	98.1	87.0	96.0	82.8	98.5	97.1	91.5

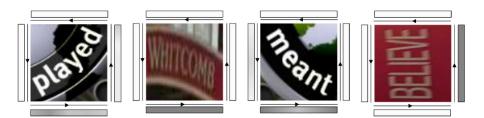


Experiment Result III

Performance on regular datasets.



Generated Placement Clues





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- position distribution

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- Horizontal position at time step t

$$x = \sum_{i=1}^{2} \sum_{j=1}^{L} j \times \textit{norm}(d_{ij})$$



Perspective











Curved











Oriented









